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Advanced control systems engineering for energy and comfort management in a building environment—A review

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ABSTRACT

Given restrictions that comfort conditions in the interior of a building are satisfied, it becomes obvious that the problem of energy conservation is a multidimensional one. Scientists from a variety of fields have been working on this problem for a few decades now; however, essentially it remains an open issue. In the beginning of this article, we define the whole problem in which the topics are: energy, comfort and control. Next, we briefly present the conventional control systems in buildings and their advantages and disadvantage. We will also see how the development of intelligent control systems has improved the efficiency of control systems for the management of indoor environment including user preferences. This paper presents a survey exploring state of the art control systems in buildings. Attention will be focused on the design of agent-based intelligent control systems in building environments. In particular, this paper presents a multi-agent control system (MACS). This advanced control system is simulated using TRNSYS/MATLAB. The simulation results show that the MACS successfully manage the user's preferences for thermal and illuminance comfort, indoor air quality and energy conservation.

Contents

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1. Introduction: problem statement

1.1. Energy

The distribution of energy consumption in European households in 1999 was as follows: 68% for space heating, 14% for water heating and 13% for electric appliances and lighting. While the percentage of space heating has decreased during the past 15 years, the percentage of consumption for the operation of electrical appliances has increased by 10–13%; representing more than half of the consumed electricity. Operation of office equipment is responsible for as much as 40% of the electricity consumed in an office building with the sector of office buildings and hence energy consumed in these buildings growing in size (Intelligent Energy Executive Agency (IEEA), http://www.iea.org).

The construction sector covers one eighth of the total economic activity in the European Union (EU), employing more than eight million people. The intense activity in building construction, in conjunction with the need for energy savings and environmental protection policy, dictate for more reasonable design practices for buildings. The newly released EU Directive "Energy Performance of Buildings" (EPBD) concerns the use of energy in buildings and urges member nations of the EU to set stricter regulations regarding the efficient use of energy in buildings. For this reason, one of the main goals of advanced control systems, as applied to buildings, is to minimize energy consumption.

1.2. Comfort conditions

In the 1970s and 1980s, the need for energy savings resulted in the design and construction of buildings that had small openings, lacked natural ventilation, etc. Because people spend more than 80% of their lives in buildings, the environmental comfort in a work place is strongly related to the occupants' satisfaction and productivity. On the other hand, as well known, energy consumption is also strongly and directly related to the operation cost of a building. Hence, energy consumption and environmental comfort conditions most often are in conflict with one another.

In the past 20 years, special emphasis has been given to the bioclimatic architecture of buildings. Bioclimatic architecture is geared towards energy savings and comfort; utilizing glazing and shadowing systems, solar spaces, natural ventilation, thermal mass, Trombe walls, cooling systems with evaporation and radiation, etc. Bioclimatic architecture focuses on the design and construction of bioclimatic buildings that take advantage and make use of solar radiation and natural air flow for natural heating and passive cooling.

The quality of life in buildings (comfort conditions) is determined by three basic factors: Thermal comfort, visual comfort, and Indoor Air Quality (IAQ) [1–4]. Thermal comfort is determined by the index PMV (Predictive Mean Vote) [2,4]. PMV is calculated by Fanger's equation [4,5]. PMV predicts the mean thermal sensation vote on a standard scale for a large group of persons. The American Society of Heating Refrigerating and Air Conditioning Engineers (ASHRAE) developed the thermal comfort index by using coding −3 for cold, −2 for cool, −1 for slightly cool, 0 for natural, +1 for slightly warm, +2 for warm, and +3 for hot. PMV has been adopted by the ISO 7730 standard [6]. The ISO recommends maintaining PMV at level 0 with a tolerance of 0.5 as the best thermal comfort. Visual comfort is determined by the illumination level (measured in lux) and by the glare that comes from direct viewing of the solar disk.

Indoor air quality can be indicated by the carbon dioxide (CO_2) concentration in a building [1,3]. The CO_2 concentration comes from the presence of the inhabitands in the building and from various other sources of pollution (NOx, Total Volatile Organic Compounds (TVOC), respirable particles, etc). Ventilation is an important means for controlling indoor-air quality (IAQ) in buildings. Supplying fresh outdoor-air and removing air pollutants and odours from interior spaces is necessary for maintaining acceptable IAQ levels. However, ventilation rates inside buildings must be seriously reduced in order to control the cooling or thermal load in an improved manner and reduce the energy load. In many cases though, this contributes to a degradation of the indoor-air quality and to what is generally known as' sick building syndrome' (SBS) [7]. For these reasons, IAQ is now a major concern in building design. Demand-controlled ventilation (DCV) systems offer an efficient solution for the optimization of energy consumption and indoor-air quality [8].

The main characteristic of DCV systems is that ventilation rates are modified according to the value of a certain parameter, for example the CO_2 concentration, which is representative of the pollutant load in a room. This technique has already been successfully applied in many cases by using mechanical ventilation. Dounis et al. [9] investigated the potential application of CO_2-based DCV to control ventilation rates for a building with natural ventilation. Simulations were performed in which window openings were adjusted based on measured CO_2 concentrations. Due to concerns over the constant variation of natural ventilation driving forces, fuzzy logic was used instead of conventional on–off or PID control. Carbon dioxide concentrations, window openings, and air temperatures are presented for a simulated day. The feasibility of such a system was demonstrated.

Wang et al. [10] developed a robust control strategy to overcome the control difficulties when DCV control is combined with economizer control. The main difficulty is the emergence instability phenomena (alternation and oscillation) in the transition phase

between different control modes. Wang et al. [11] developed an optimal and robust control of outdoor ventilation airflow rate. This strategy employs a dynamic algorithm to estimate the number of occupants in the indoor building based on the CO_2 measurement. The optimal robust control strategy achieves indoor air quality and minimum energy consumption. Hence, the second main goal and characteristic of advanced control systems is the achievement of occupants' comfort conditions.

1.3. Control objective

Living space climate regulation is a multivariate problem having no unique solution, particularly in solar buildings. More specifically, the goals of an intelligent management system for energy and comfort are as follows:

- *High comfort level*: Learn the comfort zone from the user's preference, and guarantee a high comfort level (thermal, air quality and illuminance) and good dynamic performance.
- *Energy savings*: Combine the comfort conditions control with an energy saving strategy.
- *Air quality control*: Provide CO_2-based demand-controlled ventilation (DCV) systems.

Satisfaction of the above requirements demands control of the following actuators/effectors:

- Shading systems, to control incoming solar radiation and natural light, as well as to reduce glare.
- Windows opening for natural ventilation or mechanical ventilation systems, to regulate natural airflow and indoor air change, thus affecting thermal comfort and indoor air quality.
- Electric lighting systems.
- Auxiliary heating/cooling systems.

User interactions always have a direct effect on the system under consideration in order to give the user the feeling that he or she controls his or her own environment. Users of an electric lighting system may switch the lights on or off, or may precisely choose the electric lighting level. Heating system users may change the temperature set point. An increase of the set point will immediately start the heating system as far as the indoor temperature is below this set point. Moreover, people using blinds may choose any blind position they desire.

The combined control process for the above systems requires optimal performance of almost every subsystem, under the basic assumption that each operates normally in order to avoid conflicts arising between users' preferences and the simultaneous operations of these control subsystems. Mathews et al. [12] developed cost efficient control strategies to achieve optimal energy and acceptable comfort conditions.

We could obtain optimal operation of the local controllers by using individuals who are expert operators of the system, however, this is impossible. Therefore, we need to design the architecture of a multi-agent control system that will incorporate the knowledge of such expert operators. Such a system includes an intelligent supervisor to coordinate the operation of the partial sub-systems, which are the local intelligent controllers–agents. In a multi-agent control system of a building microclimate, high priority may be given to passive heating/cooling techniques; aiming at maximization of energy conservation while incorporating the users' preferences.

A basic characteristic of the advanced control systems is their ability to operate with symbolic language and non-exact and fuzzy logic that humans perceive better. It is done in conjunction with Computational Intelligence. Techniques of this kind have been widely applied in the industry all over the world in hundreds of power plants. However, in complicated systems, mathematical modeling can hardly describe a real system in real time. For this reason, Computational Intelligence techniques, like Fuzzy Logic (human approximate classification and reasoning), Neural Networks (the neurophysiology of the human brain), and Genetic Algorithms (Darwinian evolutionary laws) have been used to solve problems that arise from the management of such systems.

The different approaches to control systems for indoor building environments can be roughly classified into the following categories: (i) conventional methods; (ii) computational Intelligence techniques; and (iii) agent-based intelligent control systems. However, it should be noted that the overlapping between categories is unavoidable. For example, genetic algorithms can tune a fuzzy controller, or a controller agent can be developed by fuzzy logic. The number of publications on the subject of control systems for building control is quite large. This being so, only a small portion of these are listed in the references. Because it is beyond the scope of this survey paper to cover all of these studies in detail, we will instead, present an overview of these categories in the next sections and focus on multi-agent control systems in more detail. Therefore, the main objective of this paper is to survey state of the art control systems in buildings and in particular, the multi agent control systems that have been recently developed.

2. Conventional control systems engineering in buildings—an overview

2.1. Classical controllers

Originally, the goal of the development of control systems for buildings was mainly minimization of energy consumption. Thermostats were used for the feedback control of the temperature [13]. In order to avoid frequent changes between the two states of a thermostat, thermostats with a dead zone were introduced and used. This kind of control is called bang–bang control with dead zone. However, overshoots in the controlled temperature were not avoided, which resulted in an increase in energy consumption. In order to solve the problem, designers used Proportional–Integrate–Derivative (PID) controllers [13,14]. Although these controllers improved the situation, improper choice of the gains in the PID controller could make the whole system unstable. Therefore, designers resorted to optimal, predictive, or adaptive control techniques.

2.2. Optimal, predictive, and adaptive control

Important research was conducted on optimum and predictive control strategies during the 1980s and 1990s. However, no industrial development has followed these scientific studies, especially due to implementation issues. In order to use optimal control [15–24], or adaptive control, [25] a model of the building is necessary. Predictive control [26,22,27–29] is very important because it includes a model for future disturbances (e.g. solar gains, presence of humans, etc.). It improves thermal comfort mainly by reducing overheating [30–32] but especially through night cooling. However, mathematical analysis of the thermal behavior of a building generally results in non linear models and even more importantly, these models differ from one building to another.

Adaptive controllers have the ability to self-regulate and adapt to the climate conditions in the various buildings. More specifically, adaptive fuzzy controllers are regarded as the most promising adaptive control systems for buildings [16,30,25]. Another way to solve the problem is by using parameter estimation methods (Recursive Least-Squares estimation). Nesler [33] developed

adaptive control of thermal processes in buildings. The standard PI control algorithm is adequate for the control of heating, ventilating, and air-conditioning (HVAC) processes. The RLS estimator provides estimates of the gain, time constant and dead time of a process. RLS estimator diverges when the control loop is subjected to an unmodeled load disturbance. Actuator nonlinearity is also a well-known limitation of self-tuning controllers. Only a few authors have directly applied adaptive techniques that learn the characteristics of a building and its environment [33,34].

Because the above optimal solutions are not always feasible, solutions that are approximate to the optimal one have been used. However, such techniques suffer from various drawbacks, some of which are:

- The need for a model of the building.
- The use of elements of bioclimatic architecture complicates the process of minimization of the cost function and if such a minimization is obtained, the results are not applicable in practice.
- The need to make parameter estimation in real time with the algorithms being used sensitive to noise. Thus, under real conditions, such techniques may give erroneous results.
- Such techniques do not deal with the problem of comfort. Nonlinear features that could determine some difficulties when monitoring and controlling HVAC equipment characterize the PMV index.
- The resulting control systems are not user friendly, since the user does not participate in the configuration of the climate of his/her environment (User preferences).
- These control methods are not use learning methods.
- The classical control maximizes the energy conservation without giving priority to passive techniques.

3. Computational intelligence in buildings

Application of intelligent methods to the control systems of buildings essentially started in the decade of the 1990s. Artificial Intelligence (AI) techniques were applied to the control of both conventional and bioclimatic buildings. Intelligent controllers, optimized by the use of evolutionary algorithms were developed for the control of the subsystems of an intelligent building [35]. The synergy of the neural networks technology, with fuzzy logic, and evolutionary algorithms resulted in the so-called Computational Intelligence (CI), which now has started to be applied in buildings. To overcome the nonlinear feature of PMV calculation, time delay, and system uncertainty, some advanced control algorithms have incorporated fuzzy adaptive control [36–39], optimal comfort control [18], and minimum-power comfort control [40]. A kind of direct neural network controller, based on a back-propagation algorithm, has been designed and successfully applied in hydronic heating systems [41].

Neural networks have been extensively used in Japan [42] where they have been applied to commercial products such as air conditioners, electric fans etc. A system of two neural networks has been incorporated in an air conditioner to further fine-tune the equipment to the users' preferences. One of the two neural networks estimates the value of the PMV index by using sensor inputs only. However, this is not always optimal for a given user. The other neural network further corrects this output. The user can train this neural network.

3.1. Fuzzy systems and evolutionary computation

The need to obtain energy savings and to guarantee comfort conditions, taking into consideration the users' preferences, drove researchers to develop intelligent systems for energy management in buildings (Building Intelligent Energy Management Systems—BIEMS), mainly for large buildings like office buildings, hotels, public and commercial buildings, etc. These systems are designed to monitor and control the environmental parameters of the building's microclimate and to minimize the energy consumption and operational costs. A large number of publications regarding the application of fuzzy techniques on BIEMS can be found in the references. The results cited are superior when compared to those of classical control systems. Recently, the practical applications of fuzzy and neural control for Heating Ventilation and Air Conditioning (HVAC) systems have been discussed with the goal being performance improvement over classical control [43–47].

The requirement for a mathematical model of the operation of a building has been an obstacle to the application of traditional control methods in buildings. In intelligent systems, namely in model-free controllers, such a model is not required. This fact is a general innovation in the development of automatic control systems. By incorporating new-type, higher-level variables that define comfort into the intelligent controllers (e.g. PMV [48]), it was possible to control comfort without going into the regulation of lower level variables like temperature, humidity and air speed. In such systems, users start to participate in the specification of the desired comfort.

Genetic Algorithms and methods coming from the theory of adaptive control are used to optimize fuzzy controllers. Fuzzy logic control has been used in a new generation of furnace controllers that apply adaptive heating control in order to maximize both energy efficiency and comfort in a private home heating system [49]. The development of fuzzy controllers to control thermal comfort, visual comfort, and natural ventilation, with the combined control of these subsystems has led to remarkable results [50,37,17,51,36,48,52–72,39].

3.2. Synergistic neuro-fuzzy techniques

Neuro-fuzzy systems originated when neural network techniques were used in fuzzy technology. Hybrid systems like ANFIS (Adaptive Neuro-Fuzzy Inference System) [73] have been used for prediction and control of the artificial lighting in buildings, following variations of the natural lighting [74]. Proper choice of the predictive control strategy, combined with a non-linear modeling of the building, the user's behavior, and the prediction of the climate parameters allowed NEUROBT system to obtain energy savings and to guarantee satisfactory comfort [27]. A neural controller, equipped with the prediction capabilities of neural networks, can be used in the control of hydronic heating systems and solar buildings [75–77,32]. Kanarachos and Geramanis [41] have proposed an Adaptive Neural Network (ANN) controller for the control of single zone hydronic heating systems. The inputs and outputs of this controller involve parameters related to the heating plant and the indoor set point temperature. However, no forecasting of either weather parameters or indoor conditions were made.

The technology of neural networks has found important applications not only to the control systems of buildings [78–81,57,46] but also to more general problems regarding renewable energy sources. Neuro-fuzzy systems have also been studied. Egilegor et al. [57] developed and tested a fuzzy-PI controller adapted by a neural network. However, it did not offer spectacular improvement. Yamada et al. [82] developed an air-conditioning control algorithm that combines neural networks, fuzzy systems, and predictive control. This system predicts weather parameters and the number of occupants. These predictions are then used to estimate building performance in order to achieve energy savings and to maintain the indoor conditions in a high comfort level.

3.3. Design of fuzzy logic and neural network controllers

3.3.1. Fuzzy P controllers

Many different methods exist to use fuzzy logic in closed-loop control. The simplest structure is to use the measurement signals from the process as the inputs to the fuzzy logic controller and the outputs of the fuzzy logic controller to drive the actuators of the process. This pure fuzzy logic system is called fuzzy P controller. The inputs of a fuzzy P controller are PMV and outdoor temperature. Auxiliary heating (AH), auxiliary cooling (AC), and ventilation window opening angle (AW) settings are the controller outputs [36,52]. These outputs, which are deterministic signals, drive the process actuators.

A global P controller has six inputs (PMV, ambient temperature T_{amb}, CO_2 concentration, change of CO_2 concentration, Daylight Glare Index (DGI), and illuminance (ILL)), and four outputs (AH/AC, SHaDowing, Artificial Lighting, and window opening angle (AW)) [39,65]. Triangular and trapezoidal membership functions are used to cover the input–output universe of discourse. In the rule design, priority is given to passive techniques to obtain indoor comfort. During moderate seasons, the fuzzy rules allow natural cooling through window openings in order to reach thermal comfort by using natural ventilation. During winter and summer, windows are kept closed to avoid thermal losses. The solar gains are controlled to allow passive heating during the winter and cut off excessive heating during the summer.

Indoor illuminance fuzzy rules are designed to give priority to the natural lighting. The electric lighting is on when indoor illuminance is zero, i.e. during nighttime and during cloudy conditions. When indoor illuminance is increased, the electric lighting is immediately turned off and shading regulates the indoor visual comfort. The performance index in the building control system is minimization of energy consumption [67].

3.3.2. PI-like fuzzy logic controllers

Fuzzy PID controllers are classified into two major categories, according to their structure [83,84]. The first category of fuzzy PID controllers involves typical fuzzy logic controllers (FLCs) realized as a set of heuristic control rules. In order to be consistent with the nomenclature [85] and to distinguish from the second category of fuzzy PID controllers, we will call FLCs in this category PID-like (PI-like or PD-like) FLCs. Most of the research on fuzzy logic control design refers to this category [86–90].

The second category of fuzzy PID controllers is composed of the conventional PID controllers in conjunction with a set of fuzzy rules and a fuzzy reasoning mechanism to tune the PID gains online [91]. Controllers of this type can adapt to varying environments. The main disadvantage of a control system of this category is that it is mainly model-dependent, since it requires human experience with controlling the plant in order to define the range of the proportional gain.

In most cases, the fuzzy PI controller is an incremental controller. The conventional fuzzy PI controller is described by the equation $u(k+1) = u(k) + \Delta u(k)$ (Fig. 1) where k is the sampling instance and $\Delta u(k)$ is the incremental change in controller output determined by fuzzy rules. PI-type FLCs most commonly are followed by PD-type FLCs. In a proportional–integral (PI) controller, proportional (P) and integral (I) actions are combined to take advantage of the inherent stability of the proportional controllers and the offset elimination ability of the integral controllers. PD-type FLCs are suitable for a limited class of systems. They are not suitable when measurement noise and sudden load disturbances exist. PID-type FLCs are rarely used because of the difficulties associated with the generation of an efficient rule base and the need for tuning its large number of parameters.

It is natural to use an incremental controller when, for example, the actuator is a motor or a valve. It is an advantage that the controller output is driven directly from an integrator, because it is easy to deal with wind up and noise. The fuzzy PI controller uses as inputs the error signal and its change (Fig. 1).

The advantage of a fuzzy PI controller is that it does not have an operating point. The control strategy of rules evaluates the difference between the measured value and the set point and also evaluates the change of this difference in order to decide whether to increment or decrement the control variables of the building. A fuzzy logic controller can implement nonlinear control strategies. If comfort condition (PMV) is 'cold', the increment will be strong, regardless of its tendency, but if the PMV error is small, the tendency is taken into account. Table 1 shows the rule base of a PI controller in a table format.

3.3.3. A combination of FLC, neural controller, and PID controller

In the illuminance controller, a cascade control strategy is used [71]. This strategy contains a main illuminance fuzzy controller and a PID controller as an auxiliary controller. The illuminance process is in close dependency with the external solar radiation changes, which can be very unpredictable or oscillatory. With the use of the cascade control strategy, which is complement to the feedback control, the performance of the corrective action of the roller blind is improved. The main fuzzy controller determines the proper position of the roller blind in order to maintain the inside illuminance at the desired value. The auxiliary PID controller manipulates the signal for proper alternation of the roller blind, to nullify the error between the current and the desired position. Two filters, realized in filter blocks, are included to smooth possible fast and frequent movements of the roller blind, that happen when external solar radiation changes occur frequently. Proper setting of the filter time constants results in smoother roller blind alternations. We want to avoid excessive movements of the roller blind, for the simple fact that it is annoying to the occupants. Curtis et al. [25] developed a neural controller that gradually undertakes the control of HVAC processes from a PID controller. In [92] Curtis and

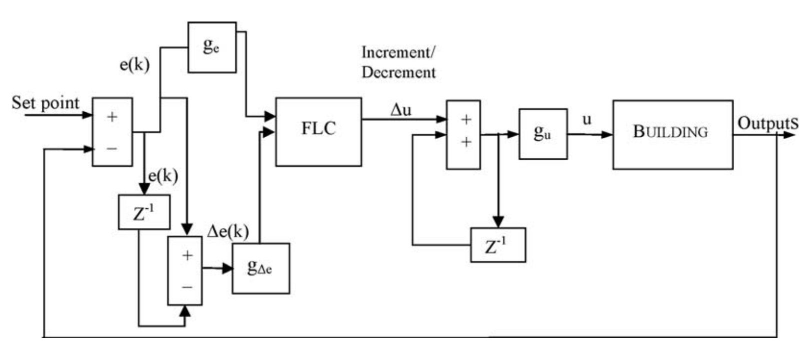


Fig. 1. Structure of fuzzy PI controller.

Table 1
The rule base of a fuzzy PI controller [85].

Δe	e						
	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NM	NS	NS	ZE
NM	NB	NM	NM	NM	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PS	PM	PB
PM	NS	ZE	PS	PM	PM	PM	PB
PB	ZE	PS	PS	PM	PB	PB	PB

Shavit a neural controller was used to augment the output of a PI controller. This controller attempts to modify the output of a PI controller in a way that the motion of the actuator is minimized. Such a combination is suitable for non-linear HVAC systems.

3.3.4. Adaptive fuzzy PD and fuzzy PID controller

The structure of the adaptive fuzzy PD controller is the same as for the fuzzy PD controller. The difference is that the adaptive fuzzy PD controller uses a second-order system as a reference model for the determination of the scaling factors of the controller. The objective is to design an adaptive fuzzy PD controller such that the behavior of the controlled building remains close to the behavior of a desired model. The adaptive fuzzy PD controller is based on scaling factors g_e and $g_{\Delta e}$ and g_u (Fig. 1) in order to improve the system's response [39].

Calvino et al. [37] add an adaptive network to the model in order to improve some general characteristics of a classical PID regulation system. Furthermore, they modified some control rules, aiming at determining a monotone "control surface" to guarantee better stability features of the system [93]. The addition of the adaptive network to the original model allows us to vary the values of the parameters regarding the integrative and derivative blocks: so doing, these parameters will depend on the peak of the "step response", which improves the stability of the entire system.

3.3.5. Neural network controllers

In thermal comfort control [46] and in the temperature control of hydronic heating systems [41], direct neural network controllers (NNC) are used. These controllers are practical and contrary to the indirect neural network controllers, they do not require the identification model of the plant. Fig. 2 shows the structure of a two-layer multi-input and single-output (MISO) neural network controller [46]. The controller has two inputs and one output: e is the error between PMV set value and feedback value, $\dot{e}$ is the error derivative, and u is the control signal to the building.

The equations of neural network controller are

$$\upsilon = w_{11}e + w_{12}\dot{e} + w_{13}b$$

$$u = \phi(\upsilon) = \frac{1}{1+\exp(-\upsilon^2)}$$

$$\Delta w_{ij} = -\eta\frac{\partial E}{\partial w_{ij}} = -\eta\cdot\frac{\partial E}{\partial \mathrm{PMV}}\cdot\frac{\partial \mathrm{PMV}}{\partial u}\cdot\frac{\partial u}{\partial w_{ij}} = \pm\eta^*\cdot\frac{\partial E}{\partial \mathrm{PMV}}\cdot\frac{\partial u}{\partial w_{ij}}$$

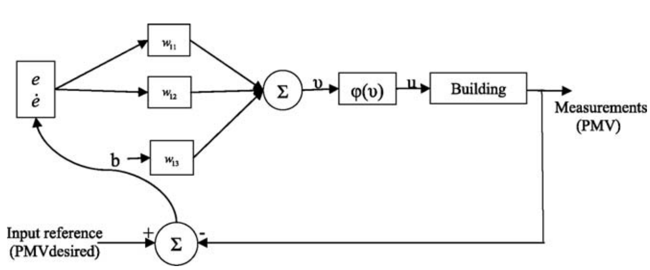


Fig. 2. A direct neural network controller.

where υ is the input to the output layer of NN; w_{11} and w_{12} are the synaptic weights; w_{13} is the synaptic weight of the fixed input (bias) $b = 1$; $\varphi(\upsilon)$ is the activation function (unipolar sigmoid function); u is the output in the output layer; and η^* is the learning-rate parameter. Training of a neural network is essentially the regulation of its weight coefficients in a way that minimizes a cost function. The determination of the weights of the interconnections between the neurons is based on the gradient descent algorithm. At the beginning, the algorithm assigns random values to the weights of the network. The two signals at the input of the controller are obtained and the output u of the controller is computed. Next, the algorithm updates the weights of the network, as well as the new output signal u, which is then supplied to the building.

3.4. Tuning of fuzzy logic controllers

It is important to distinguish between the problems of tuning and of learning in an FLC. Tuning is mainly concerned with the optimization of an existing FLC, whereas learning constitutes an automated design method for fuzzy rule sets. Tuning processes assume a predefined rule base and their goal is to find a set of optimal parameters for the membership functions or for the scaling factors (normalized gains). These gains are used to map the actual inputs and outputs of the FLC on the normalized universe of discourse [−1, +1]. Learning processes perform a more elaborate task while searching in the space of possible rule bases and do not depend on a predefined set of rules. The most important optimization techniques are:

1. Tuning of the scaling factors for the control inputs and outputs that can be achieved by a set of *meta-fuzzy rules*. This approach has a trial and error nature. A good example can be found in [94,95,47].
2. Parameterized control parameters (scaling factors and membership functions) adapted by *Genetic Algorithms* to a fitness function that specifies the design criterion in a quantitative manner [96].
3. A formal approach to the derivation of the scaling factors, aiming at establishing an analytical relationship between the values of the scaling factors and the closed loop behavior of the controlled process [85].
4. The input and output universe of discourse of the FLC is normalized on the range [−1, +1]. The gains are chosen as bounds on the inputs and outputs of the controller (*trial and error*) so that the rule base represents the active region on the control actions:

$$g_e = \frac{1}{\max(e)}, \qquad g_{\Delta e} = \frac{1}{\max(\Delta e)}, \qquad g_u = \frac{1}{\max(u)}$$

5. The choice of gains is done with an *on-line auto-tuning* strategy [97]. Let the maximum values of the two fuzzy controller inputs during the last T_A seconds be $\max_{T_A}\{e(kT)\}$ and $\max_{T_A}\{\Delta e(kT)\}$. We define the maximum gain values as

$$g_e = \frac{1}{\max_{T_A}(e)}, \qquad g_{\Delta e} = \frac{1}{\max_{T_A}(\Delta e)}$$

3.5. Optimization of fuzzy logic controllers

The gradient-based optimization technique determines search directions for minimization of an objective (or error) function. We can use this technique to minimize energy consumption in distributed environmental control systems without increasing the occupants' thermal dissatisfaction [98].

There are several such derivative-free techniques, the most popular of which are: Genetic Algorithms (GAs), simulated annealing, random search and downhill simplex method. GAs are adaptive search and optimization algorithms that work by mimicking the principles of natural genetics [99]. These algorithms are, however, very different from traditional search and optimization methods that are used in engineering design problems. Fundamental ideas are borrowed from genetics and are used artificially to construct search algorithms that are robust and require minimal problem related information.

Dounis et al. [51] developed a GAs-based optimization technique for fuzzy controller for thermal and indoor air quality in buildings. Kolokotsa et al. [66] have proposed an optimization strategy that integrates in a Genetic Algorithm the indoor comfort requirements with the energy consumption, targeting to satisfy the indoor comfort requirements and simultaneously minimize the energy consumption. The solution of the Genetic Algorithm provides the optimal indoor comfort settings that are then fed into the controller as new set points.

In [62] the objective was to develop and test user adaptive controllers for blinds, electric lighting and heating. For this purpose, an integrated control system that adapts to the characteristics of the environment and the building was developed and successfully implemented. The system was built on three nested control levels: level 1 where the system translates physical values into actuator commands; level 2 where the fuzzy logic controllers are implemented; and level 3 where adaptation aspects are dealt with. User adaptation was performed by means of GAs that optimize the parameters of the fuzzy logic controllers. GAs have shown to be the most efficient optimization method for this task. An important result cited in the paper is that because the automatic control system did not satisfy user desires, they rejected it at a high percentage rate (25%), compared to the user adaptive system.

Alcala et al. [100] used GAs to develop smartly tuned fuzzy logic controllers for heating, ventilation, and air conditioning systems, taking into account energy performance and indoor comfort requirements. Also, Lam [101,29] proposed a classifier system with GAs in on-line control for an air conditioning system. The target of this control system is to make the air conditioning controller a self-learning control system.

3.6. Supervisory control

Optimal control aims to preserve indoor environmental conditions with minimal energy expenditure under dynamic outdoor and indoor conditions. It can be achieved by using local controllers of the sub-systems and optimal supervisory control of the building. For the advanced control systems in buildings, supervisory control is an interesting subject. The set-points are reset by the controller supervisor due to the changes of the outdoor/indoor loads, the users preferences, and the energy consumption. Kolokotsa et al. [66] developed optimization techniques based on Genetic Algorithms targeted at optimal indoor comfort settings. These new settings are directly applied to the controllers. Wang et al. [19] developed an on-line control strategy for an air-conditioning system using digital control for VAV (variable air volume) AHUs (air handling units). A genetic algorithm is used to detect the optimal settings of the controllers. This strategy predicts the system response to the changes of the control set-points using on-line parameter identification and self-tuning. Dounis et al. [55] developed an intelligent coordinator of fuzzy controllers–agents for indoor environment control in buildings using 3D fuzzy comfort set. In this system, the basic factors that participate in the control of indoor environmental conditions are the controllers and the users' comfort requirements. Synchronization of the control system is obtained by the design and implementation of an intelligent coordinator, which is a centralized one. It consists of a master agent and a slave agent that are both implemented by fuzzy logic theory. The master agent evaluates the energy efficiency of the building and comfort of occupants. A fuzzy inference mechanism produces signals that activate the slave agent and change the set points of the controllers. The slave agent is a fuzzy negotiation machine (FNM), which synchronizes the interaction of the fuzzy controllers and manages to avoid conflicts between them. When some conditions determined by the slave agent are satisfied, fuzzy controllers are activated, otherwise they stay inactive.

3.7. User interfaces

In smart buildings, the building automation systems and control networks (BACnet) [102] provide user interface devices (thermostat, valves, keypads) so that the user can interact with the components of each function (heating, cooling, ventilation, shading, security). The system allows users by setting their preferences (desired comfort conditions, energy management, and occupancy schedule).

Kolokotsa et al. [103] uses a smart card unit (kiosk), manufactured by the French company INGENICO that performs the interface between the system and the user. The users' preferences are monitored via the smart card unit. Considering the users' preferences collected from the smart card unit for a specific time, such as one week, a statistical analysis is performed evaluating the average users' preferences corresponding to the three indoor comfort controlled variables: PMV index, indoor illuminance and CO_2 concentration.

Keyson et al. [104] proposes a mixed-initiative user interface that is an intelligent thermostat that can reduce energy consumption. An embedded statistical model uses living patterns to infer user intentions.

In practice, however, fully usable user interface systems are undefined and unrealized [105] for many reasons. A user interface device is difficult to use in different buildings. Each building has different equipment, control systems and requirements. Even in buildings with the same systems, the environment within which they operate cannot be foreseen.

Penner and Steinmetz [105] developed a Dynamic Interface Generation for Building Environments (DIGBE) that dynamically adapts to the user and data environments.

The mentioned control systems are listed in Table 2. We summarize the most important technical issues regarding the classical and advanced control methods. In the column of energy consumption, the symbol $\surd$ denotes that the advanced control strategies can achieve significant energy savings compared with the classical control systems. The energy savings percentage depends on weather conditions, building characteristics and user preferences.

4. Agent-based intelligent control systems

Various researchers define Artificial Intelligence (AI) in different ways. The differences in the definition of AI have two dimensions: One is human centrality and the other is rationality. The aspect that intelligence deals with rational actions is mostly adopted. In this view, intelligence deals with the approach to the problems through the laws of thinking; in other words, through clear processes of reasoning (Aristotelian reasoning). The rational approach results in systems that are a combination of mathematics and technology. Thus, AI involves systems that operate rationally.

Table 2
Comparison of control systems.

Control systems	Thermal comfort control (PMV)	IAQ control (CO_2)	Visual comfort control (illumination)	Energy consumption	Global control strategies	Priority to passive techniques	User preferences	Learning	Tuning: fuzzy systems or GA or neural adaptation	Temperature control	Adaptation	DCV ventilation control	Source of reference
ON/OFF	–	–	–	–	–	–	–	–	–	√	–	–	[13]
PID	–	–	–	√	–	–	–	–	–	√	–	√	[13]
Fuzzy P control	√	√	√	√	√	√	–	–	–	–	–	√	[36,68]
Fuzzy PID control	√	√	√	√	√	√	–	–	–	–	–	√	[67]
Adaptive fuzzy PD	√	√	√	√	√	√	–	–	–	–	√	√	[67,37]
Fuzzy systems	√	√	√	√	√	–	√	–	–	–	–	–	[72]
Fuzzy PI control	√	√	√	√	√	√	–	–	√	–	–	√	[55]
Adaptive fuzzy PI	√	√	√	√	√	–	–	–	√	–	–	√	[37,57]
Neural network control	√	–	–	√	–	–	–	√	–	–	–	√	[41,46,75,76]
Agent-based intelligent control	√	√	√	√	√	√	√	√	√	–	√	√	[112,116,121,123,117]
Predictive control	√	–	–	√		√		√		–	–	√	[27,82]
Supervisory control	√	√	√	√	√	√	√		√	–	–	√	[10,11,44,66,117]
Reinforcement learning control	√	√	√	–	√	√	√	√	–	–	–	√	[118,119]
Ambient intelligent	√	√	√	√	√	–	√	√	–	–	–	√	[69,120,121]
Self-adaptive control system	√	√	√	√	√	√	√	–	√	–	–	√	[61–63]
Optimal control	–	–	–	√	–	√	–	–	–	√	√	√	[22]
Optimal and robust control	–	√	–	√	–	–	√	–	–	–	–	√	[19]

In the approach of AI through the laws of thinking, emphasis is given to the correct derivation of conclusions. Best results are achieved when rational action is applied and this can be done by using rational agents. A rational agent acts in a way that is optimal in regard to either the clarity or ambiguity of the information that it accepts. Consequently, the use of rational agents is fundamental in the AI approach. A rational agent that realizes the best possible action in a given situation is an intelligent agent.

In controls and robotics, intelligent agents are designed and implemented. In automatic control, a controller has the characteristics of an intelligent agent. The properties of the environment are very important and have significant implications on the design of controllers and rational agents. Classical automatic control systems deal with environments that are causal and observable. In stochastic and observable environments, optimal stochastic control is applied, and in environments that involve both continuous and discrete time subsystems hybrid control is applied.

At the AI lab of Massachusetts Institute of Technology (MIT), Brooks and his group [106] work on an intelligent room project that focuses mainly on the user and the facilities offered to him/her in the room. For this reason, cameras, microphones, etc. are installed in the building to control voice, monitor faces and gestures, etc. This is a new research direction in control systems buildings. In the various zones of the building, controllers are considered as distributed software agents [107]. Intelligence is distributed to agents and evolves through the connections and interactions of the agents.

4.1. Multi-agent control systems (MACS)

Many times, control engineers face complicated control problems where they have to design and implement real time control systems that use a group of controllers instead of a single one. In addition, the human factor is involved in the control system, either rewarding or not rewarding a specific control strategy (reinforcement learning). These systems are called Human Centric Systems [108]. Now, the control engineer has one more job to do: that of breaking the problem into many simple sub-problems (structuring). The design of the multi-controller system is performed and the system is implemented on a more general framework, based on controllers–agents. For optimal operation, the controllers–agents are guided by a coordinator–agent [109].

As we stated in the previous paragraphs, in order to control the users' environment, researchers have followed various approaches; e.g. neural networks based on the conventional theory of mechanical learning. However, these approaches use objective functions that aim either at deriving a minimized control function that satisfies the users' needs on an average level, or at optimization between a numbers of conflicting needs (e.g. energy efficiency and users' comfort). In both cases, users have limited participation in the operation of the system and for this reason; they must tolerate some degree of discomfort.

One solution to this problem is offered by combining systems based on behavior (behavior-based systems) with systems based on Computational Intelligence [106,110,111]. The main advantage of the systems that are based on behavior is that they reject a theoretical model and replace it by the real one. The behavioral system is a fuzzy controller where a genetic algorithm regulates the knowledge basis and the membership functions. The fuzzy controller's outputs are weighted by the coordinator and then forwarded to the actuators.

The control systems that have been developed by using classical techniques of AI are automated but not autonomous. The word autonomous comes from the Greek words "auto" (self)

and "nomos" (rule or law). A system is autonomous when its behavior changes following a fundamental law. For example, biological systems are autonomous because they operate with mechanisms like self-organization, evolution, adaptation and learning. Methodologies and techniques developed for intelligent autonomous systems, like mobile robots, have been transferred to and applied to buildings in order to equip them with intelligence [106,112]. In [112] the authors have developed a multi-agent system based on fuzzy logic and genetic algorithms. The system consists of three constant behaviors: (a) security, (b) danger and economy, and (c) a comfort behavior adapted to the action and behavior of the habitants.

4.2. Architecture of a multi-agent control system in buildings

Techniques that divide a problem into smaller sub-problems, which are consequently solved, are called divide-and-conquer techniques [113]. They also constitute a top-down process. In general, there are no standard or classical methods to optimally divide a problem in smaller sub-problems. Each complex problem has its own peculiarities and its analysis may reveal the appropriate ways to perform the task. Therefore, people try to invent heuristic techniques to do the job.

In this case, we solve the sub-problems by designing controllers–agents that are based on fuzzy logic and can be optimized by using genetic algorithms. An intelligent supervisor [54] coordinates the operation of the controllers–agents. It is an important procedure because it leads to the normal operation of the entire system. In other words, it solves the original problem.

The concept of an Intelligent Agent (IA) has been introduced recently in the area of computer science [114]. It has been used extensively in the field of Artificial Intelligence and is closely related to the subject of distributed problem solving [113,115]. An IA consists of a virtual entity (software) that mainly has the following properties:

(a) It has the ability to communicate and interact with its environment.
(b) It is able to perceive the local environment.
(c) It is guided by basic "objectives".
(d) It has feedback behaviors.

The design of a multi-agent control system consists roughly of three steps [115]:

1. *Structuring*: Decompose the whole problem into a set of independent partial problems.
2. *Solving individual sub-problems*: Solve the partial problems by designing controllers–agents that know how to solve the partial problems.
3. *Combining individual solutions*: Combine the set of implemented agents into a coherent whole by properly coordinating their activities.

4.2.1. Decomposition of the problem of energy efficiency and comfort in buildings

The goal of obtaining comfort conditions and simultaneously energy conservation in a building is solved by the development of intelligent systems. Mo and Mahdani [116] developed an agent-based framework for building operators and individual occupants to negotiate their control activities. Dounis and Caraiscos [54] proposed the use of an intelligent supervisor that coordinates the optimal cooperation of the local controllers–agents. The result is that total control is achieved, occupants' preferences are satisfied, conflicts are avoided and energy consumption is conditionally minimized. In a building, the controlled variables are the Predictive Mean Vote (PMV) index, the Illumination level (lux), and the CO_2 concentration (ppm). The actuators that are being used are the auxiliary heating/cooling system, the mechanical ventilation, the shading, and the electric lighting.

In order to control the entire operation of the building, five local intelligent field controllers are developed and optimized off-line by using Genetic Algorithms. These five lower level controllers are guided by a higher level Intelligent Coordinator. The idea is presented in Fig. 3.

Inputs and outputs of the local controllers are

Controllers FCA_1 and FCA_2—*Inputs*: illumination error and its rate of change; *Outputs*: control signals to the shadowing and electric lighting.
Controllers FCA_3 and FCA_4—*Inputs*: PMV error and its rate of change; *Outputs*: control signals to the heating/cooling system.
Controller FCA_5—*Inputs*: CO_2 concentration and its rate of change; *Outputs*: control signal to the mechanical ventilation.

The communication operation of a controller–agent with its environment is sketched in Fig. 3. For each controller–agent FCA_i, $i = 1–5$ there is the activation signal $w_i = f(\text{inputs}_i, q_i)$, where variable q_i denotes the state of the controller–agent, and the acknowledge signal α_i that makes the controller–agent active ($q_i = 1$) or inactive ($q_i = 0$).

In each sampling period (time step), the controller–agent performs a set of communication tasks. First, it receives a sample of measurements and uses it to calculate the activation signal w_i and send it to the coordinator/supervisor. This signal denotes that the controller wants to become active or inactive. When the coordinator receives activation signals from all the controllers–agents, it makes its decision and sends acknowledge signals back to them. If a controller–agent receives a positive acknowledge signal, it becomes or stays active; otherwise it becomes or stays inactive. Also, if a controller–agent is active, it calculates the control action and sends it to the actuators.

4.2.2. Structure of the intelligent coordinator

The proposed intelligent coordinator is shown in Fig. 4. It receives as inputs PMV, IAQ, illumination level, energy consumption, occupants' preferences, and activation signals from the controllers–agents. It then performs two specific tasks using a master-slave coordination mechanism. Each task requires a separate intelligent agent. The dependency between the two tasks is that the lower level agent (slave) operates only when it receives an activation signal ρ from the upper level agent (master) [109,115]. Inputs_1: Predicted energy consumption, and total comfort [55]. Inputs_2: E_{PMV}, ΔT_{out}, E_{lin}, E_{lout}, ΔE_{out} where E_{lin} is the indoor illuminance desired minus total indoor illuminance, E_{lout} is the illuminance desired minus outdoor illuminance, ΔE_{out} is the change of outdoor illuminance (k)–outdoor illuminance $(k-1)$,

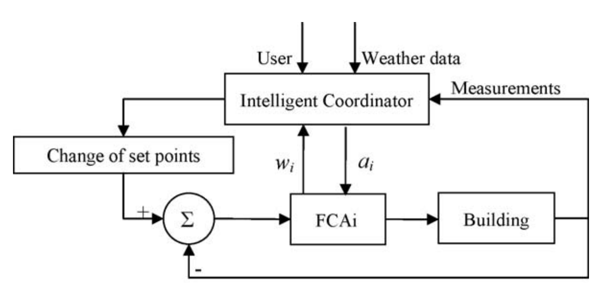


Fig. 3. Block diagram of the controlled system, the controllers–agents, and the intelligent coordinator.

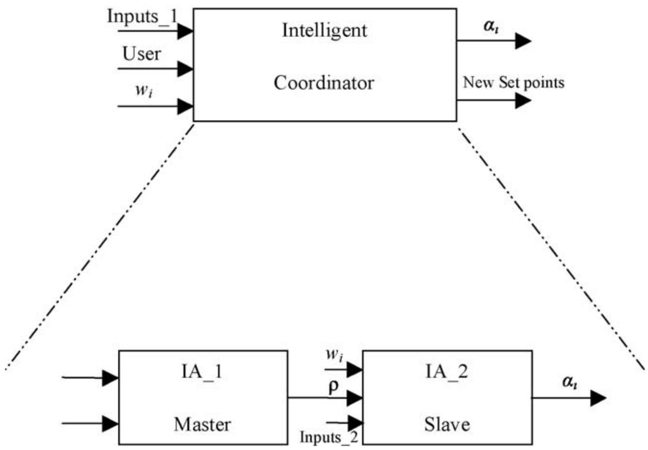


Fig. 4. Structure of the intelligent coordinator.

E_{PMV} is the error of PMV and $\Delta T_{out} = 23^0 - T_{out}$, and T_{out} is the outdoor ambient temperature.

- The first IA (IA_1), called master agent, evaluates the energy efficiency and comfort of the building and monitors the occupants' preferences. By equipping the master agent with qualitative fuzzy rules, the inference engine machine produces new set points. Activation signal ρ makes active or inactive IA_2. The rules that are used have the form IF–THEN, for example,

  IF Predicted Energy is small AND Comfort is low THEN Change of set points. More details can be found in the paper Dounis–Caraiscos [55].
- The second IA (IA_2), called slave agent, compensates the interaction of the controlled sub-systems and manages to avoid conflicts between them; as for example, between natural ventilation and mechanical cooling, natural ventilation and heating, shadowing and heating or cooling, decrease of direct solar radiation and visual comfort, etc. Very often, evaluation of the control strategy is based on subjective criteria. Therefore, IA-2 uses linguistic rules that stem from physical laws [48,53] and an inference engine that generates a compensation policy. This policy is decisive as to the increase of the system's performance. Slave agent IA_2 consists of two Fuzzy Negotiation Machines (FNMs) [55]. An example of a rule used by FNMs follows:

  If E_{lin} is (NE or PO) and E_{lout} is (NE or ZE) and ΔE_{out} is ZE then a_1^{NP} is OFF and a_2^{NP} is ON.

  If E_{PMV} is NE and ΔT_{out} is NE then a_3^{NP} is OFF and a_4^{NP} is ON and a_5^{NP} is ON.

where $a_i^{NP}(k)$ are the output from FNM 1 and FNM 2, and $a_i(k)$ is the acknowledgement signal. For more see Ref. [117]. The two IAs can be viewed as parts of an integrated real time decision support system that derives compensation actions in order to increase energy efficiency of the building, minimize the conflicts that arise from the simultaneous operation of the controllers and satisfy the occupants' preferences by obtaining thermal and visual comfort.

The above analysis shows that intelligence of the entire system is embedded not only in the controllers–agents but also mainly in the structure of their communication.

4.2.3. Organization diagram

The result of the design of a multi-agent control system is a hierarchical organization of intelligent agents, called the organization diagram. In essence, the organization diagram is a model that represents the operation of a multi-agent control system. Fig. 5 shows the organization diagram of the overall control algorithm for the control problem in a building environment, where a master–slave coordination mechanism is adopted. Intelligent agent IA_1 is the master agent and intelligent agent IA_2 is the slave. The organization diagram exposes the interaction between sub-problems, which is confronted by the coordination mechanism. In the lower level, coordination is local with dynamic priority. The priority of each field controller is decided by IA_2.

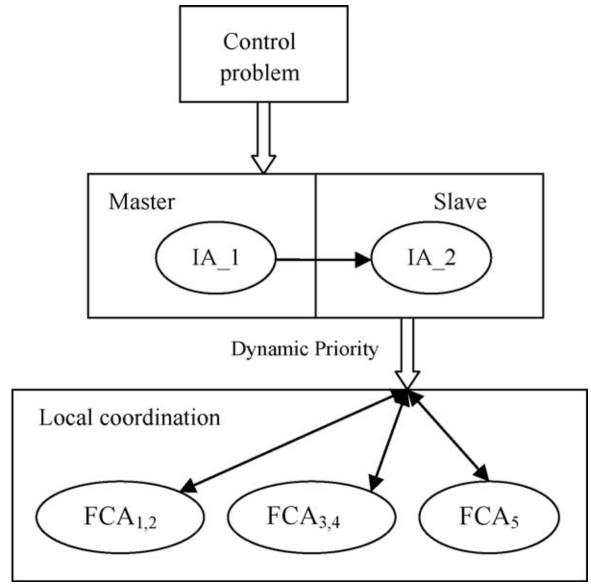


Fig. 5. Organization diagram of the proposed control algorithm.

4.2.4. Uncertainty in user's preferences using α-level set

The desired value or set point is chosen as a trapezoidal fuzzy interval whose membership function is illustrated in Fig. 6. The trapezoidal type-1 fuzzy set equipped by an α-cut level can effectively model the uncertainty of comfort [117].

The core is composed of the most acceptable user's preferences and the fuzzy interval is defined as

$$[x^a_{d_-}, x^a_{d_+}] = [x^0_{d_-} + a(x^1_{d_-} - x^0_{d_-}), x^0_{d_+} - a(x^0_{d_+} - x^1_{d_+})]$$

The desire values belong to interval $[x_d - \delta^a_{x_d}, x_d + \delta^a_{x_d}]$, x = {PMV, CO_2, ILL}, where x_d is the set point, x_{d_-} and x_{d_+} denote the upper and lower bounds of x, respectively, and $\delta^a_{x_d} = x^0_{d_+} - a(x^0_{d_+} - x^1_{d_+})$ is the band around the desired value. The α-cut of fuzzy desired values is

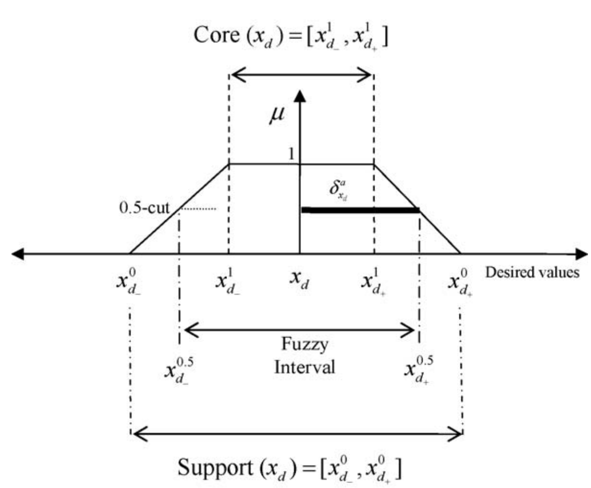


Fig. 6. Trapezoidal fuzzy interval desired values.

the set of all values of x_d satisfying the user's preferences at least with a degree of preference or acceptance $\alpha = 0.5$. We have chosen $\delta^{0.5}_{\mathrm{PMV}_d} = 0.4$, $\delta^{0.5}_{\mathrm{ILL}_d} = 75\,\mathrm{lx}$, $\delta^{0.5}_{\mathrm{CO}_{2_d}} = 50\,\mathrm{ppmv}$.

4.2.5. Computing the membership grade of measurements PMV, ILL, and CO_2 using α-level fuzzy set

The fuzzy α-cut or α-level fuzzy set of A characterized by

$$\tilde{A}_\alpha = \begin{Bmatrix} A(x) & \text{if } A(x) \geq \alpha \\ 0 & \text{otherwise} \end{Bmatrix} \quad \text{or} \quad \tilde{A}_\alpha \equiv \{(x, \mu_A(x)) | x \in A_\alpha\}$$

Based on the above definition, we can conclude that α-level fuzzy set is obtained by reducing part of the fuzziness in the original fuzzy set [117].

In each iteration, the membership grades of the measurements PMV, ILL, and CO_2 are computed by the α-level fuzzy set (Fig. 7). These grades determine a point in a fuzzy cube.

4.2.6. A 3D fuzzy model for global comfort

The unit cube geometry of discrete fuzzy sets assists us when we define fuzzy concepts. The comfort is represented as an information granule; the size of granules is problem-oriented and user-dependent. In particular, the size of information granule of the comfort consists of three parts (PMV, ILL, CO_2), and the formal representation of this information granule is a fuzzy set in a fuzzy cube [55]. Therefore, a 3D discrete fuzzy set models higher level uncertainty than does a Type-1 FS. This technique opens up an approachable way for modeling human decision-making.

Let Ω be a set of three elements $\Omega = \{\mathrm{PMV}_d, \mathrm{CO}_{2_d}, \mathrm{ILL}_d\}$. The nonfuzzy power set 2Ω contains eight sets. These sets correspond respectively to the eight bit vectors (0, 0, 0), . . ., (1, 1, 1). Empty set $\varnothing$ lies at the origin (0, 0, 0) of the cube, and space Ω lies at vertex (1,1,1). The 1 and 0 s indicate the presence or absence of the ith element in the subset. A fuzzy subset $c \subset \Omega$ defines the fuzzy unit (fit) or fit vector:

$$c = \underbrace{(\mu_{\mathrm{PMV}^\alpha_d}, \mu_{\mathrm{CO}^\alpha_{2d}}, \mu_{\mathrm{ILL}^\alpha_d})}_{\text{point in fuzzy cube}} \in I^3 = [0,1]^3$$

$$\mu_c = [\underline{c}, \bar{c}] \subseteq [0,1]$$

$\underline{c}$ and $\bar{c}$ denote lower and upper bounds, and μ_c denotes an interval set, that is, the set of the real numbers from $\underline{c} = \alpha$ to $\bar{c} = 1$.

The fuzzy α-cut set of measurement variables PMV(k), ILL(k), $CO_2(k)$ defines a 3D fuzzy comfort set c with membership function μ_c. If $\alpha = 0.5$ then the 3-D fuzzy set is a cube with origin (0.5, 0.5, 0.5) and the optimal comfort value corresponds to the vertex (1, 1, 1). Using the symmetric fuzzy equality measure [117] we measures the degree to which fuzzy set c matches fuzzy set Ω, that is, the membership grade of 3D fuzzy comfort set:

$$E(c, \Omega) = \mu_{c(k)} = \mathrm{Degree}(c = \Omega) = \frac{\mathrm{cardinality}(c \cap \Omega)}{\mathrm{cardinality}(c \cup \Omega)} = \frac{\sum_{i=1}^{3} \min(c_i, \Omega_i)}{\sum_{i=1}^{3} \max(c_i, \Omega_i)}$$

where k is the discrete time step. The fuzzy equality measure $E(c, \Omega)$ measures the degree to which fuzzy set c equals fuzzy set Ω.

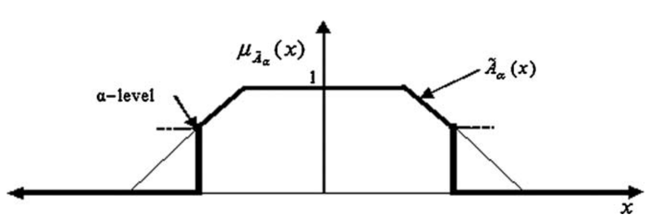


Fig. 7. The α-level fuzzy set of fuzzy set A.

If c and Ω are nonempty then $E(c, \Omega) = E(\Omega, c) \in [0, 1]$, $E(c, c) = 1$ and $E(c, \varnothing) = 0$. The fuzzy equality measure gives a value near 1 if the two fuzzy sets equal well. It gives a value near 0 if they equal poorly. The 3D fuzzy comfort set is a new representation for the word "comfort" [117]. This methodology of approximation representation of the comfort is very significant because it is used in the procedure of decision-making for the master agent.

4.2.7. Simulation results

A trapezoidal MF is defined as a quadruplex {a, b, c, d} where these parameters (with $a < b \leq c < d$) determine the coordinates of the four corners of the trapezoidal MF. In particular, the users' preferences for comfort conditions are specified via trapezoidal fuzzy sets with the membership functions of the form:

T_1 (PMV; $\mathrm{PMV}_d - 0.5$, $\mathrm{PMV}_d - 0.3$, $\mathrm{PMV}_d + 0.3$, $\mathrm{PMV}_d + 0.5$).
T_2 (ILL; $\mathrm{ILL}_d - 100$, $\mathrm{ILL}_d - 50$, ILL_d, $\mathrm{ILL}_d + 50$, $\mathrm{ILL}_d + 100$).
T_3 (CO_2; $\mathrm{CO}_{2d} - 75$, $\mathrm{CO}_{2d} - 25$, CO_{2d}, $\mathrm{CO}_{2d} + 25$, $\mathrm{CO}_{2d} + 75$).

where, as usual, the parameters denote the characteristic points of the piecewise membership functions of the fuzzy sets (see Fig. 6). The first, one trapezoidal form T_1, can be regarded as a descriptor of user's preference regarding the PMV, where $\mathrm{PMV}_d = 0$. The second form, T_2, characterizes the user's preference regarding the illuminance, where ILL_d = {800–600–500–800} lx. The last one, T_3, describes the user's preference of CO_2 concentration, where CO_{2d} = 1000 ppmv. In the simulation example the α-cut of fuzzy desired values is $\alpha = 0.5$. The simulations concerned a passive solar building characterized by an important south-facing window, glazed area (3 m^2), area 45 m^2, volume 135 m^3 and by a high thermal inertia, light transmittance of the window glazing mean ($\tau = 0.817$), reflectance of all indoor surfaces ($\rho = 0.4$) [117]. In the TRNSYS there is an electric lighting (10 lamps), a shading device (curtain) and heating/cooling actuator. Simulation time step is 6 min.

The performance of the agent-based intelligent control system applied in a single zone building is evaluated. Some significant results (16 July) are shown in Figs. 8–13. Figs. 8–10 present time histories for of the PMV index, illuminance and CO_2. These figures illustrate that the comfort conditions are maintained within the acceptable limits of the users' preferences. Fig. 11 shows the time evolution of membership grade of new fuzzy comfort variable within the 3D fuzzy comfort set with degree of acceptance >0.65. Fig. 12 gives the curves of the daily and predicted energy consumption. Energy consumption and comfort usually affect

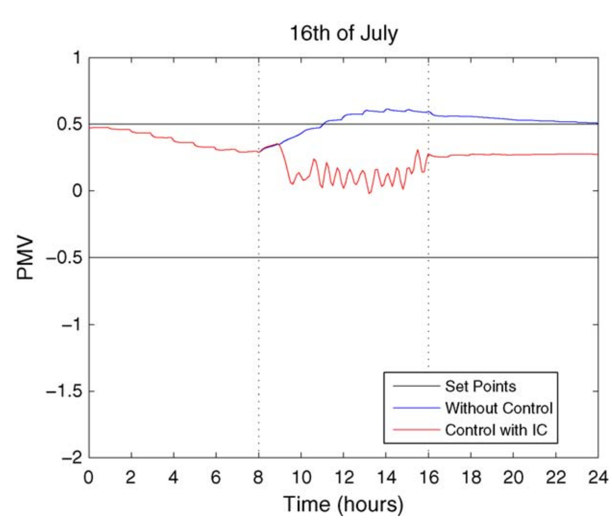


Fig. 8. Time history of PMV.

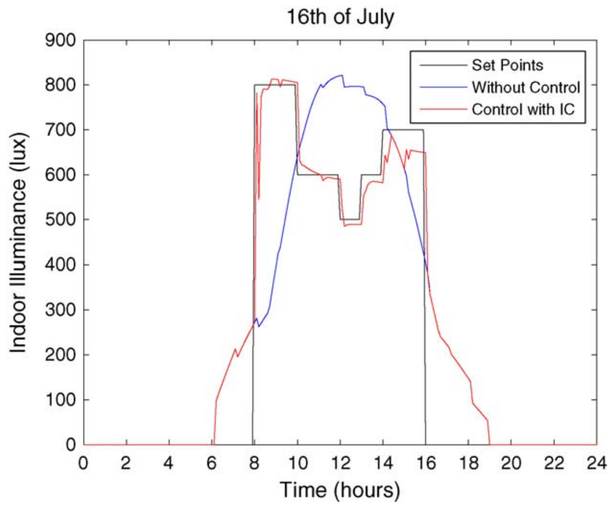


Fig. 9. Time history of indoor illuminance.

each other in opposite ways. The optimized agent-based intelligent control system improves occupant's comfort while the energy savings is significant. Fig. 13 presents time history of the PPD. These simulation results indicate that the Percentage of People Dissatisfied (PPD) index [4] is less than 6% and therefore it is maintained within the acceptable limits (below 10%).

4.3. Reinforcement learning agent

Dalamagkidis et al. [118] have developed a reinforcement-learning controller that takes into account user preferences in order to achieve energy savings, high comfort and indoor air quality. The advantage of this approach is that the reinforcement-learning agent continuously learns from different characteristics of the buildings and improves its policy. However, this reinforcement controller temporarily increases users' dissatisfaction and total energy consumption.

Anderson et al. [119] used a reinforcement-learning agent in parallel with an existing feedback PI controller. This combination is designed within a robust control framework. Its main goal is to improve the control of a non-linear model of a heating coil. The results show that the reinforcement learning agent learns how to modify the PI controllers' output only when the PI controller in not adequate to satisfy the control objectives.

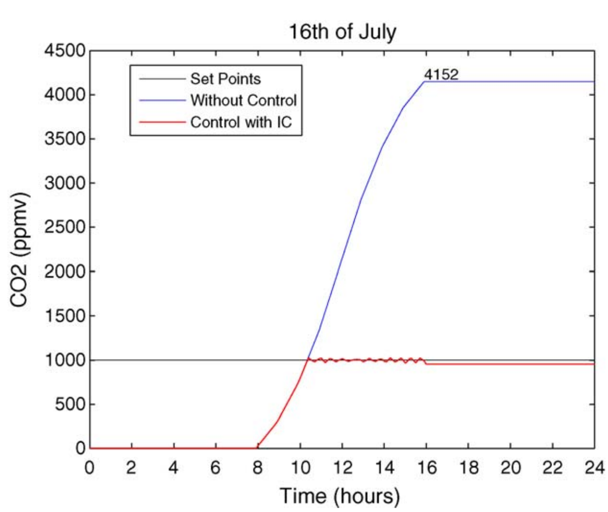


Fig. 10. Time history of CO_2.

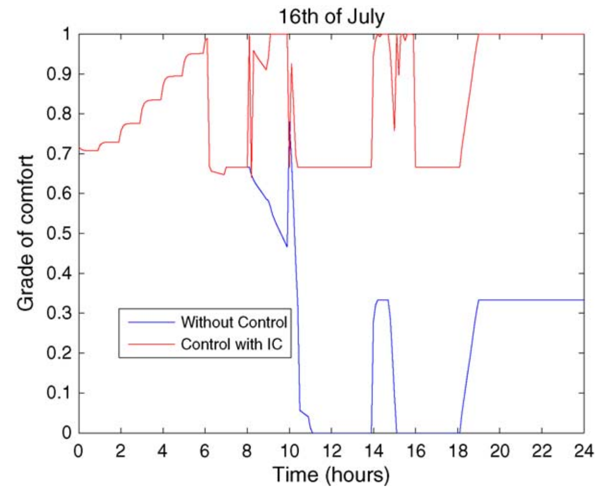


Fig. 11. Time evolution of comfort.

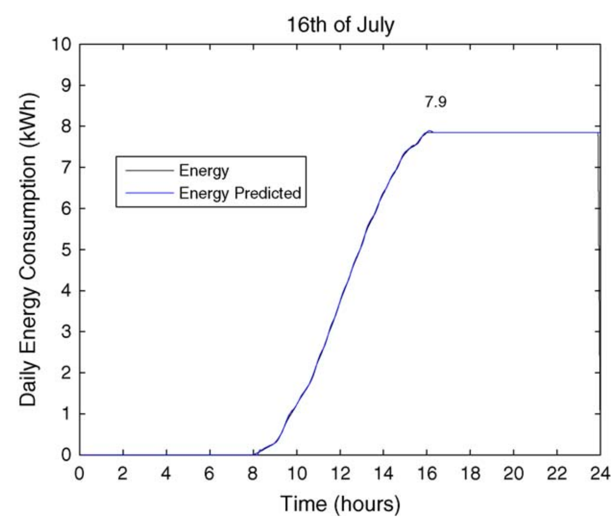


Fig. 12. Time history of the daily real and predicted energy consumption.

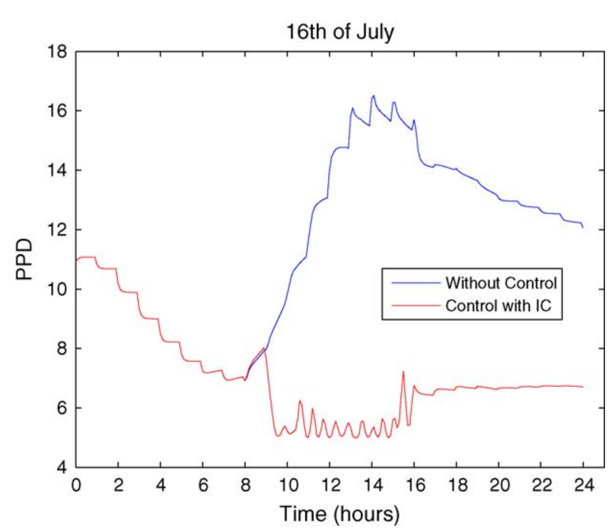


Fig. 13. Time history of PPD.

4.4. Ambient intelligence—AMI

In [106,107,120,121,69,122,123], the authors deal with the scenario of "Ambient Intelligence—AmI". AmI is a new paradigm in information technology that "triggers" imagination. It is a digital environment that perceives the presence of users and adapts to their needs, depending on their behavior. In such environments, interconnected intelligent fuzzy agents are used. These agents support the users' actions and the effectors of the building. Experiments performed at Essex intelligent dormitory showed that this system could approach the idea of an Intelligent Environment.

5. Conclusions

5.1. The survey

In this article, we presented a review of control systems for energy management and comfort in buildings. At the beginning of this paper, we defined the problem as a whole, where energy, comfort and control are involved. Next, we presented conventional control systems for buildings and their disadvantages. The development of intelligent control systems in the framework of computational intelligence has set the basis for improving the efficiency of control systems in buildings. New ways of designing human-centric systems arose from the development of the scientific field of computational intelligence. Application of such systems to buildings results in the so-called "intelligent buildings".

The architecture of a multi-agent control system for energy efficiency and comfort in a building environment was then presented. In finishing, we referred to a new paradigm in information technology, Ambient Intelligent, which is a new approach towards the creation of an intelligent building environment. Implementation methods for multi-agent control systems are Fuzzy Logic, Neural Networks, Neuro-Fuzzy Systems, Markov Chain Models, Finite State Automata, Learning Automata, Dependencies Organization, etc.

A comparison has been made between different advanced control techniques. The main comparative results are:

- The fuzzy PI (or fuzzy P) control algorithm is adequate for the local controllers.
- The tuning of the fuzzy PI controller could be achieved on-line with fuzzy system [50] and off-line with genetic algorithms [100].
- In intelligent coordinator level could be used predictive control giving priority to passive techniques to achieve comfort.
- Based on users' preferences, the optimum tuning of set-points of the controllers is achieved by supervisory control technique.
- The on-line learning of the control system with reinforcement learning method.
- All mentioned advanced control systems satisfy the indoor requirements within acceptable limits and simultaneously achieve a considerable reduction in energy consumption.
- By using these advanced control systems, high comfort levels and energy savings can be obtained. It should also be mentioned, however, that there are some limitations in practice. For example, the user's activity level and thermal resistance of clothing, involved in the PMV equation, cannot be measured by sensors. The cost reduction of the PMV sensor would have a great potential for the HVAC application [46].
- Advanced control systems are defined as intelligent control systems, and include two levels. The first level is a low-level feedback control of indoor conditions for each building's zone. The second level is a high-level supervision (intelligent coordinator) and planning. This high-level management provides optimal operation strategies for energy conservation and environmental comfort. Therefore, an advanced control system represents a basic structural unit in an integrated indoor environment and energy management system.

5.2. Future perspectives

Future trends and open questions that are more general are given here.

1. Energy Issues, Other Factors (Weather, Building Design, Occupancy, etc.), Thermal comfort issues, Passive Solutions (Architectural and Structural Design), Naturally Ventilated and Mixed Mode Buildings.
2. Hierarchical and supervisory control structure using autonomous agents—'divide and conquer' approach.
3. Balance between thermal comfort and energy usage.
4. Hybrid control theory that can be used to design a supervisory controller. The task of a supervisory controller involves the optimal control-based set point policy generation.
5. Agent–controller methodology from artificial intelligence can be used for coordinated task achievement. Learning paradigms for agents:
   - learning feed forward random neural network [124];
   - random neural networks with reinforcement learning [124];
   - adaptive stochastic finite-state machines [125].
6. Ambient Intelligence Systems.
7. Open-Loop Coordinator of Local Controllers.
8. Closed-Loop Real-Time On-line Learning Ability.
9. Type-2 fuzzy sets [126], order-2 fuzzy sets [55] or Routh sets supporting the development of higher, conceptually composite concepts for comfort, user preferences, and energy.
10. Granular Computing (GrC) as a new paradigm of Computational Intelligence in user-centric systems [108]. The collection of complex information entities (thermal comfort, visual comfort and indoor quality) can be considered as an information granule.
11. The decreasing cost of hardware and improvements in software will make the wireless sensor–actuator networks very useful in the comfort control of buildings [127].

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